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An Integrated Repainting System for Digital Restoration of Vijayanagara Murals

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An integrated repainting system is proposed in this paper for digital restoration of images of heritage murals, which have historical significance in their painting styles and ritualistic contents. The repainting system uses an ensemble of conventional image processing tools, in tandem with some state-of-the-art image rendition techniques, such as scaled bilateral filtering, source-constrained inpainting, tonal processing, and texture mapping based on gradient fusion. Murals that are old by nearly four centuries, have been imaged *in situ* from the walls of temples under a controlled environment, and then they have been fed to our repainting system. As the work of mural art is highly subjective, and so is its interpretation, a battery of tests for subjective evaluation has been performed to compare the different stages of restoration. Three different tournament strategies have been followed to make the test result devoid of any subjective bias as far as possible. The overall evaluation result is quite encouraging, as the restored images exhibit a gradually improving quality through the different stages of restoration.

Keywords: Digital image restoration; heritage art; heritage murals; mural inpainting.

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1. Introduction

Most of the Indian temples in general, and South-Indian temples in particular, are filled with vividly colored paintings on their ceilings and walls. These paintings are considered to be in the genre of historical paintings, as they depict the epics of mythology and the glory of their period. They aid to the understanding of cultural diversities, social interests, art and architecture, economic conditions, and many such information related to the period of their casting.[1,2]

Vijayanagara dynasty, which ruled the Southern India in 1336–1646 AD, gave prime importance for exalting their art and architecture. The figures of deities

painted by the Vijayanagara artists possess a vibrant, ritualistic combination of various styles and idioms, and they are mostly framed within cusp-like arches. Ensembles of individual depictions of these compositions are based on different mythological events. This legacy of sculpture, architecture, and painting influenced the development of arts long after the empire came to an end.[1–4] Even after nearly four centuries of its disestablishment, the remnants of the artwork still stand as astonishing masterpieces.[3,5] Many murals and artworks can be seen on the ramparts of temples and palaces in their capital city, Hampi, in the state of Karnataka, India, and also at Lepakshi in the state of Andhra Pradesh, India. This paper is particularly concerned with digital restoration of such colored murals.

A restricted set of tonal colors was commonly used for painting the murals in the temples during the Vijayanagara period.[1] An initial outlining was done by a light color, such as yellow or red, on which flat tonal colors like yellowish brown and ochre were added.[2,4] The plasters were merely left exposed, and the background was usually painted in brilliant red or ochre. As a final touch, black outlines and white highlights were added to complete a composition.

Several works may be found in the literature, which deal with restoration of damaged frescoes. For example, the work in Ref. 6 is on restoration of faded colors by color clustering and analysis of color-changing patterns of pigments over time. Another work by Ref. 7 focuses on enlargement and enhancement of photographic prints of old frescoes, to convey sufficient details of the samples in the digital versions of the fresco images. In all these existing works, the art samples of frescoes/murals under consideration are not only different in theme and composition from the mural paintings considered in our work, but also differ in terms of the cause and level of degradation. For example, some of the external damaging factors like soot accumulation, influence of physical elements, etc. are specific to climate variations and customs followed locally. Our integrated approach is to take into account all these temple-specific damaging factors, thereby providing a better means of digitally restoring the century-old heritage mural images, which have a high socio-historic value.

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1.1. *Motivation of our work*

Many heritage murals have been renovated in India under several cycles over centuries. Though these renovations were based on the earlier compositions, they could not retain the originality. In addition, frequent damages to these paintings have led to reduced periods of renovation cycles. The reasons for the observed damages are many. Since the paintings are made on plasters, they are very much prone to get etched off with aging and dust accumulation. Burning of camphor and incense sticks, and fire worshiping were performed during religious ceremonies. On account of these over years, black soot has deposited on the paintings. It is now a tedious task to manually renovate the murals on regular basis. Moreover, frequent physical renovations may diminish the originality sooner or later.

The objective of our work is digital repainting and restoration of the mural paintings, which are so badly degraded that further deterioration may result in complete loss and impossibility in retrieval. As these mural images bear a rich cultural heritage, their artistic rendition by today's artists has a high socio-historical impact in the genre of history painting. Our computer-assisted technique can provide a visual cue to the artist for understanding and harnessing the styles and details while recreating the artwork with originality and confidence. An artist can consider the image of the original work, which is highly degraded now, as well as our digitally repainted result, and can then recreate the painting as a probable replica of the original work. Subjective knowledge of the artist comes into play with a stronger confidence when the digitally repainted image is provided to him (her) in addition to the original image.

To explore the advantage of the integrated technique, we seek a professional artist to recreate few samples of mural painting. The artist at first recreates the artwork based on his artistic perception from the original image only (*original recreation*). Then, the same artist is provided with our digitally repainted image. Based on the information available from the original and our digitally repainted images, he recreates the artwork again (*enhanced recreation*). The latter recreation is much clearer, as confirmed by the artist and his co-artists. Also, the artist says that the repainted image indeed provides better visual cues for the recreation process. The time and effort taken for inferring the visual content of paintings are also considerably less. The original recreation and the enhanced recreation corresponding to a sample mural are shown in Fig. 1.

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1.2. *Data acquisition*

The majority of images in our study have been collected at and around Hampi, the past capital of Vijayanagara kingdom. The images used for our experimentation, some of which are presented in this paper, are those of murals on the ceilings of Virupaksha temple of Hampi. Various methods of heritage imaging, like reflectance transformation imaging and multi-spectral imaging, have been discussed in the literature.[8–13] Most of them are based on relighting and require scaffolding equipments. However, in our acquisition process, we could not use any artificial lighting and scaffolding as per the stricture from the conservation authority. For obtaining the digital images of murals, we were permitted to use only two high-resolution DSLR cameras of resolution 10M pixels and 18M pixels. All the images have been captured by us in natural daylight, with maximum usable aperture number to keep the entire scene in focus. Since the murals are painted in the interiors of ceilings and walls of the temples, it was difficult to snap a properly illuminated shot due to limited light. This difficulty has somewhat been tackled by using long exposures (1/10 s) and lower aperture number (5.6), wherever tripod stands were allowed to collect the data. At those places where tripod stands were not allowed, maximum tolerable exposure (1/30 s) with higher aperture number (8 to 12) has been used. The latter

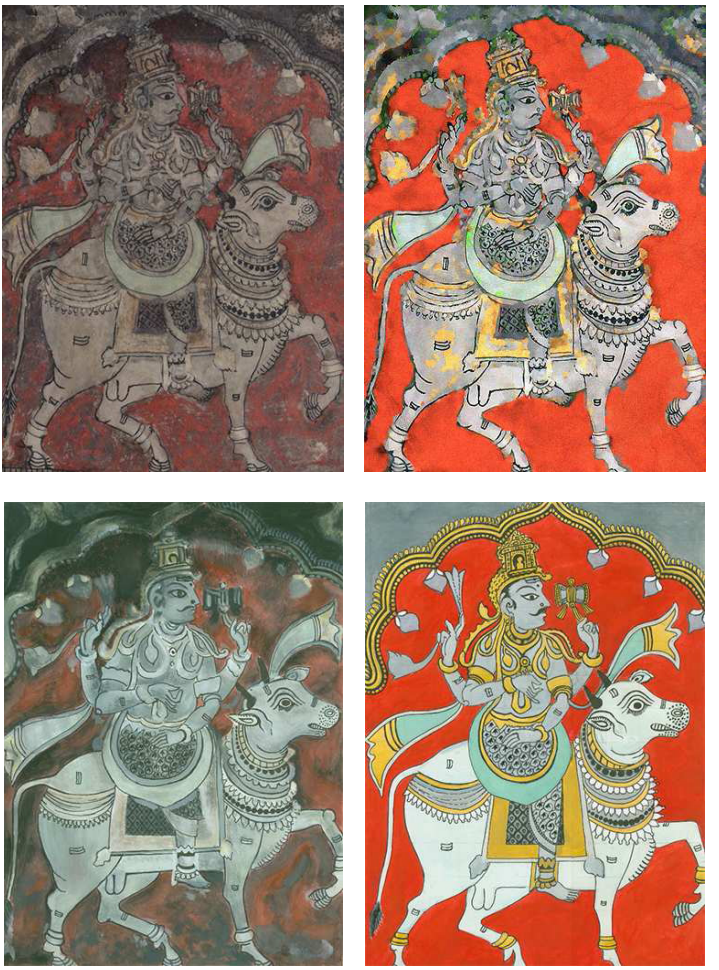

Fig. 1. Top left: Original image of a mural (PASHUPATI). Top right: Digitally repainted image. Bottom left: *Original recreation* by the artist, considering only the original image. Bottom right: *Enhanced recreation* by the artist, considering both the original and our digitally repainted images.

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resulted in comparatively poor quality of the acquired image due to noise, camera shake, and blur, which has later been taken care of in the preprocessing stage of our algorithm. The camera ISO has been set to 100 in all cases to strike a balance between the image clarity and the digitization noise.

2. Overview of the Integrated Approach

The repainting algorithm presented in this paper is an integration of various image processing techniques like enhancement, denoising, segmentation, digital inpainting, image sharpening, color correction, tonal processing and texture fusion. A brief overview of the integrated work is shown in Fig. 2. In the preprocessing stage, an

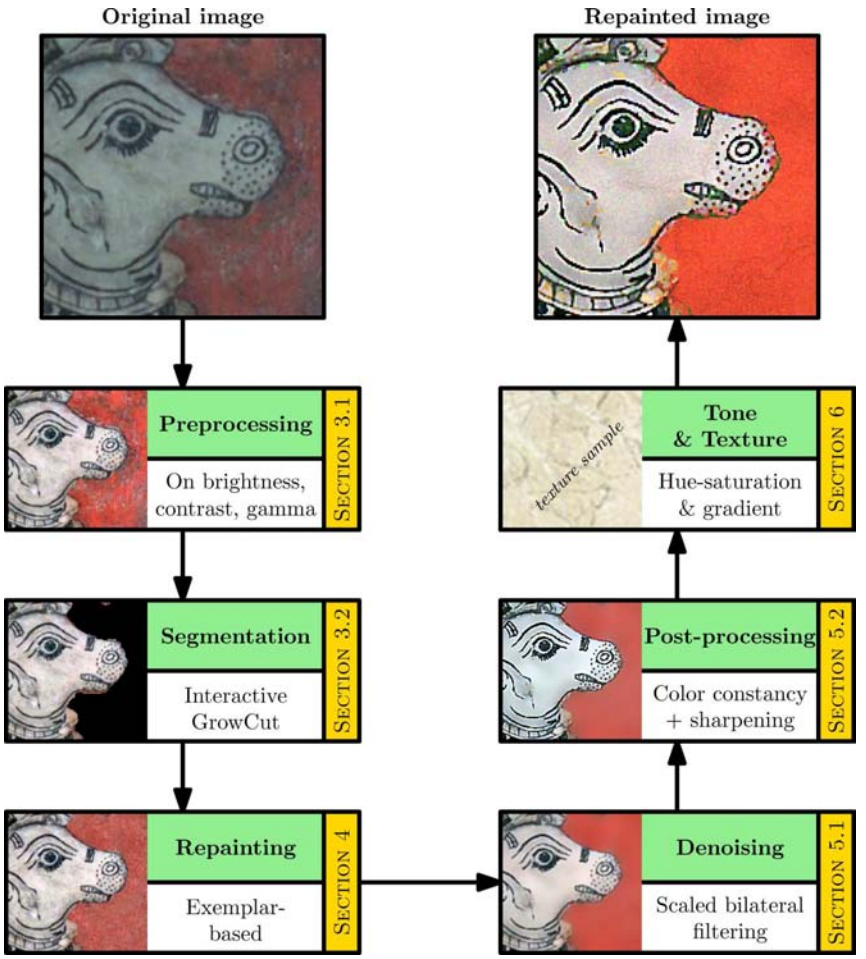

Fig. 2. A schematic overview showing the proposed integration of the different stages.

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enhancement procedure is applied, which includes brightness and contrast adjustment, followed by gamma correction, in order to take care of the poor illumination, as images are captured beneath the pyramidal structure of the temple. Denoising is accomplished by *scaled bilateral filtering*.[14] Segmentation is achieved by *cellular-automata-based interactive multi-label image segmentation algorithm*.[15] All these are described in Sec. 3.

Digital repainting is carried out by an effective *exemplar-based inpainting* technique with source constraining, which is an extension of inpainting as region-growing method.[16] As explained in Sec. 4, the inpainting is used to restore (with user supervision) faded and eroded portions in background and foreground.[17] This may cause certain artifacts, which are suppressed by *scaled bilateral filtering*. In the post-processing, image sharpening is done by *unsharp masking*,[18] while color correction

is performed using a *color constancy* algorithm.[19] These are discussed in Sec. 5. The color-corrected image is subjected to tonal processing by computing the dominant hues in CIE-XYZ color space,[20] assuming the colors in the image to be flat tonal colors.[1] To beget the realistic effect of murals painted on stones, texture synthesis is carried out, and its subsequent blending with the processed image is performed through *gradient-based fusion*.[21–23] Section 6 describes the overall idea of tonal processing and texture fusion. All these are performed to enhance the image quality without degrading the pictorial content of the subject, which is one of the most significant aspects in visual art processing and analysis, and emphasized in contemporary works in areas of fine arts.[24] Hence, we have also carried out a detailed experimentation on *subjective evaluation* using a system based on *tournament strategy*,[25] and the proposed system is found to perform well in restoration of mural images, as shown in Sec. 7.

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3. Preprocessing and Segmentation

3.1. *Preprocessing*

Digital images of murals, usually taken in low light, suffer from under-exposure, poor contrast, and are sometimes affected by sensor noise. Hence, at first the overall brightness is increased, and then the contrast is enhanced by global histogram stretching of the image luminance as a linear function.[18,26,27] Next, gamma correction is made to provide a natural appearance.[18,28] The gamma values (ranging from 0.6 to 1.4) are determined empirically, accounting for the variations in illumination during data acquisition. An example of adjusting brightness, contrast, and gamma correction is shown in Fig. 3. The sensor noise is suppressed by bilateral filtering,[29]

Fig. 3. Left: Original image. Right: Preprocessed image with $\gamma = 1.12$, brightness factor $= 30$, and contrast range $[0, 255]$.

as explained in Sec. 5. In addition, the noise emphasized during histogram stretching is also suppressed, by retaining much of the structure details.[30] For our data, it works well mainly for two reasons: (i) noise content is highly localized in images, and (ii) stretching of noise intensity is much less compared to that of the structure details. The noise due to aging and other natural distortions are taken care of in later stages, as discussed in Sec. 5.

3.2. *Segmentation*

The idea of performing segmentation for processing of heritage images has been proposed in Ref. 31 in order to render different mosaic styles. In that work, a statistical region merging algorithm has been used to detect relevant boundaries in an image, and then mosaic tiles were placed along the boundary directions to emphasize them. It has also been shown that color reproduction of different mosaic styles (particularly, *opus vermiculatum*) can be achieved successfully. We also employ a similar strategy of separating the foreground from the background of a mural image to process them individually. As the mural images are excessively noisy amidst their detailing, intricacies, and ornamentation, we found that a fully automatic segmentation performs much below the desired level while separating an object from its background. Hence, we have adopted a cellular automata based interactive segmentation algorithm called GrowCut.[15] It is a semi-automatic segmentation method where a user marks some strokes (seed strokes) distinctively in the regions to be segmented. Primarily there are only two regions to be partitioned, namely the background and the foreground. Some markings are made by the user in the foreground as well as in the background by two predefined distinguishing colors. The process of segmentation then proceeds iteratively. In some images, ambiguous regions are observed where it is difficult even for a human being to distinguish between foreground and background on the basis of mere color or intensity. Placing more seed strokes in such ambiguous regions by closely marking near the contours, as observed in particular for the current application, can yield better result.

It may be noted that, unlike conventional graph-cut[32] segmentation methods, the GrowCut algorithm does not necessarily specify hard segmentation constraints. Instead, the scope of providing soft user-specified segmentation constraints in GrowCut ensures smoothness of the object boundary. On the contrary, in graph-cut algorithm, due to initial tobogganing and resultant over-segmentation, object boundary estimation may not always result to actual object borders. Hence, GrowCut is found to be more suitable for an interactive segmentation of degraded mural images. The segmentation of foreground and background is made to avoid an unwanted intrusion from one to the other during the inpainting process. The noise being similar in background and foreground regions, the general inpainting process may result in appearance of artifacts in either of the regions. Segmenting the foreground and the background isolates one from intervening into the other during the process of inpainting, which are carried over both regions individually.

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4. Repainting

Digital image inpainting is a process of interpolating the missing portions of an image by taking into account its surrounding information in the concerned image in a perceivably plausible form.[33,34] In the context of our work, the noisy regions in mural images are marked to be the missing regions. Denoising algorithms normally used for elimination of general kinds of noise[18] fail to perform satisfactorily when a region is largely washed by the affecting noise. Such a situation is better handled by a digital inpainting algorithm by forming holes (empty regions surrounded by informative pixels) over a noisy region and then interpolating these holes with surrounding information.[35]

Out of different inpainting techniques, the texture-growing technique to fill up the holes can restore the textures satisfactorily but cannot restore large object contours and structures.[36] For interpolation of small regions, a mask-based technique can be used, which considers the neighboring pixel values in the mask for interpolation.[37] Another technique proposed in Ref. 38 can restore the structural features like edges and object contours efficiently, but fails to achieve satisfactory texture preservation. The technique in Ref. 39 decomposes the filling-up process into two separate tasks, one for restoration of structures and another for texture synthesis; however, as the area of filling increases, the filled region continues to get blurred.

To address the aforesaid issues, an exemplar-based inpainting algorithm is proposed in Ref. 16, which simultaneously imbibes the efficacy of structure recreation and texture synthesis. The filling-up process is guided by prioritizing the patches along the edges of the holes. The dependency of inpainting process on the order of filling up the holes forms the basis of exemplar-based approach. Hence, the act of prioritizing is made by examining the neighborhood. To improve the runtime of the algorithm, a measure of step length for the search region is defined.[40] The digital inpainting algorithm considered in our repainting work resorts to the exemplar-based approach. Such an approach is preferred over other inpainting approaches in the context of our repainting work, since the foreground of a mural needs to be sharp and clear, thereby delivering a significantly enhanced information, not less than the original image. However, the inpainting process induces some noise in the background region, which are cleaned later in the process of bilateral filtering (Sec. 5).

Continuing with notational conventions similar to earlier works,[16,37,38] the entire preprocessed image (including both inpainted and source regions) in our work is represented by I, the region to be filled up (inpainted region) by Ω, and the source region (the region in which interpolating values are sought) by Φ. Then $I = \Omega + \Phi$, whence the source region is given by $\Phi = I - \Omega$.

Holes are created in the region to be filled (Ω), and the boundary of a hole is the fill-front of the corresponding inpainting region. As practiced in an exemplar-based algorithm, we have defined a priority term as the product of data and confidence terms to designate the priority of the pixels to be filled up. The data term captures

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the existence of a structure at the fill front, and the confidence term determines the confidence of the filled-up pixel.[16,41] The prioritized pixels, which guide the filling-up process are chosen on this fill-front. A priority for each pixel at the fill-front is computed, corresponding to the respective confidence term and data term, and the patch centered at the highest priority pixel is considered. The source region is searched for an exemplar patch, which is most similar to the highest prioritized patch. The empty pixels of the prioritized patch are filled up by those corresponding positional pixels in the exemplar patch, and the fill-front is updated with the new boundary.

With reference to the current work, the general exemplar-based inpainting algorithm, as proposed in Ref. 16, has been modified and subsequently applied for foreground and background correction in different contexts. One such modification to the inpainting process is that the source region, where the filling-in pixels are sought for, is constrained to a specific user-defined portion — a region which is perceivably less damaged — instead of either considering the entire image obtained after discarding the affected region or only the neighborhood of affected region, as source. The purpose for such constraining arises from the distinguishing characteristic properties of the image. The background region is expected to be uniform with minimal structural appearances, whereas the foreground has to be made sharp and informative with prominent structures of the corresponding characters.

Since the background uniformity is too much degraded to be hardly recognized, the restoration needs a sample region — assumed to be intact from degradation — as reference. Without a defined source, the unsegmented image would mess up the appearance after mere inpainting (considering the entire image, excluding the affected region, as source). The source constraining and segmentation in tandem avoids the intrusion between background and foreground, and ensures uniformity in the background. After scaled bilateral filtering, the artifacts in the background are found to be minimized, thereby giving the desired success of the inpainting process.

4.1. *Background correction*

The background region observed in our heritage murals are expected to have a smooth, uniform, and plain appearance. Majority of this region is badly affected by dust and soot, and the surface is disturbed considerably by spot etches and spiky noise. Some of the small portions of the background region can be perceived as satisfactorily intact. So, the restoration of a large distorted area of the background is to be ensured from this small acceptable portion. This is achieved by constraining the source region to the small, visually acceptable region.[42] The source constraining can be summarized as follows.

The inpainting of the image by selecting a target (affected) region implies the rest of the image to be the source. The evasion of searching for exemplar patches in the rejected region is achieved by introducing the constraining of source region only to those portions of the image that visually appeal as minimally distorted,

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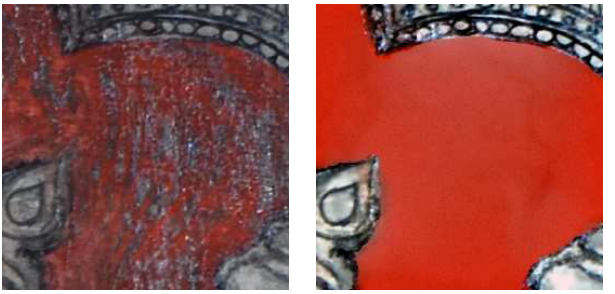

Fig. 4. Left: Original background sample. Right: Restored background sample.

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subjectively. As it is a highly subjective phenomenon, it calls for human expertise in the event to proceed further. Some regions in the source may not be distorted to the extent of any necessity to correct them, although they may not be visually perceived to be satisfactory enough to be grown into full background. Such uncertain regions are included neither in the source region nor in the inpainting region, and form the regions of the remnant image. After the source-constrained background correction, we have $I = R + \Omega + \Phi'$, where, R is the remnant image, Ω is the inpainting region, and Φ' is the constrained source region.

Thus, it is a region growing process as a special case of inpainting process, since the source is constrained to a comparatively smaller area, which is replicated over a large distorted region in a plausible way. The image in Fig. 4 shows a sample background in its original and restored forms.

4.2. *Foreground correction*

In the foreground region, the noise is in the form of local distortions like contour gap formation, etches, spikes, spot accumulation of dust, etc. which are mainly limited to small areas. This is tackled by mere exemplar-based inpainting algorithm over the foreground. The broken links of the foreground structure are inpainted satisfactorily. A basic assumption made is that, at least a small perceivable region of the background is devoid of distortions. This perceived region of background is essentially the source portion for reconstructing the damaged background. In this work, the inpainting applied to foreground and the inpainting applied to background are much different in principle, since the background correction is not merely an interpolation but a region-growing process, and the foreground is an interpolation process. In combination, they essentially form a process of repainting in an artistic manner where clearly perceived portions of an artwork are retained as in the original and the portions of acute ambiguity are left to the interpretation of the artist.

The justification for choosing source constrained inpainting, against general inpainting,[16] is the achieved uniformity in background and consistent structures in foreground, under subjective process, as shown by the images in Fig. 5.

Fig. 5. Comparison between general inpainting (middle) and source-constrained inpainting (right), with reference to original image (left). The effect of intrusion of undesired colors and structures could be observed in general inpainting.

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5. Denoising and Post-Processing

5.1. *Denoising*

Bilateral filter is a nonlinear weighted averaging filter, mainly used for image denoising.[30,43] As ordinary bilateral filtering imparts a blurring effect, denoising is done through scaled bilateral filtering to eliminate spot noise and inpainting artifacts — the former during preprocessing and the latter during post-processing.[14] Scaled bilateral filter computes the spatial and range-parametric Gaussian functions by considering the image at different scales prior to computation of Gaussian weights. The Gaussian spatial weight, with spatial parameter σ_s, is computed as in the conventional bilateral filter. The Gaussian range weight, with range parameter σ_r, is computed by scaling the image with a scale parameter, σ_G.

The scaled bilateral filter, represented as $G_{FG}(\mathsf{p})$, is formalized as

$$G_{FG}(\mathsf{p}) = \frac{\sum_{\mathsf{q}\in K} G_s(\|\mathsf{q}-\mathsf{p}\|)G_R(|I_G(\mathsf{q})-I(\mathsf{p})|)I(\mathsf{q})}{\sum_{\mathsf{q}\in K} G_s(\|\mathsf{q}-\mathsf{p}\|)G_R(|I_G(\mathsf{q})-I(\mathsf{p})|)}, \tag{1}$$

where, $G_s(\cdot)$ is a function that spatially controls the influence of other pixels over current value, given by

$$G_s(\|\mathsf{q}-\mathsf{p}\|) = \exp\left(\frac{-\|\mathsf{q}-\mathsf{p}\|^2}{2\sigma_s^2}\right), \tag{2}$$

where K is the neighborhood of current pixel p, and $G_R(\cdot)$ is the scaled range function given by

$$G_R(|I_G(\mathsf{q})-I(\mathsf{p})|) = \exp\left(\frac{-|I_G(\mathsf{q})-I(\mathsf{p})|^2}{2\sigma_r^2}\right). \tag{3}$$

Here, $I_G(\mathsf{q})$ is the pixel value of scaled image, which is essentially Gaussian-convolved original image. The Gaussian convolution at location p is given by

$$I_G(\mathsf{p}) = \sum_{\mathsf{q} \in K} G_G(\|\mathsf{p} - \mathsf{q}\|) I(\mathsf{q}), \tag{4}$$

where $G_G(\cdot)$ is a two-dimensional Gaussian kernel whose neighborhood is defined by the scaling parameter, σ_G, as follows:

$$G_G(d) = \frac{1}{2\pi\sigma_G^2} \exp\left(\frac{-d^2}{2\sigma_G^2}\right). \tag{5}$$

In the context of our work, the noise eliminated by scaled bilateral filtering is mainly spot noise, such as local etches, spikes, and spot dust accumulation. The effects of speckles and glitches are also softened off by the application of this filter. The scaling parameter controls the depth of blur in the image. A large value of this parameter causes the halo effect to be predominant over the edges, which appears as blur. Further, instead of obtaining the weights of the bilateral filter over the entire image at a single scale, the background and the foreground are scaled individually at different scales, and a different set of weights are obtained accordingly. The parameter set is determined in an empirical way. Guided by the segmentation process, this renders a smooth and uniform background as desired, along with avoiding the halo effect in foreground by reducing the foreground noise.[14] The effectiveness of this filter in retaining edge information, while filtering the noise, can be observed in the residual images, as shown in Fig. 6. Though this filtering results in minimizing the noisy components present in the image, the resulting denoised image is affected with a little blur. This is taken care of during the post-processing stage.

5.2. *Post-processing*

While denoising a mural image, the filtering procedure induces some blurring effect. Also, if any light source is used during the imaging, the color of light source may affect the overall appearance of the image. These are taken care of in the post-processing stage.

The blurred image due to the filtering process is sharpened by the process of *unsharp-masking*.[18] The sharpening process compensates for blur in the image, which enhances the appearance and strengthens the edges to pose for originality.

Fig. 6. Images showing the effectiveness of scaled bilateral filtering in skimming the noise while preserving edges: (from left to right) original noisy image, Gaussian blurring result, scaled bilateral filtering result, residual image by Gaussian blurring, and residual image by scaled bilateral filtering.

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Fig. 7. Post-processing on the image PASHUPATI. Left: After scaled bilateral filtering. Right: After sharpening and color correction.

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The influence of sharpening is highlighted in the foreground region. In the background region, the sharpening has a negligible effect, since it has almost a uniform or a negligible gradient variation. Whatever be the gradient variation, to avoid undesired artifacts in the background, the background is further scaled, thereby preserving the uniformity.

The biased appearance of the image by a light source used during imaging is removed by applying a technique for recovering the color constancy. The technique is based on "gray world assumption" of color rendition.[19] The restored image obtained by sharpening, followed by the color constancy algorithm, is shown in Fig. 7. As a final step, the processed image is again subjected to the basic enhancement technique of brightness and contrast adjustment to account for perception influenced by the filtering process.

6. Tonal Processing and Texture Fusion

6.1. *Tonal processing*

To take care of fading of flat tonal colors, we analyze the mural images in normalized CIE-XYZ color space, with $W(x_w = 0.310, y_w = 0.316)$ as the *white point*, to detect the prominent color components and their extent of saturation.[20] Each color C is represented as (x_c, y_c, Y_c), where x_c and y_c are the chromatic components and Y_c is the luminance component. We compute the *hue* as the angle made by **WC** with x-axis, and the *saturation* as the magnitude of **WC**, as shown in Fig. 8. The values lying within a distance of s_{th} from W are considered as achromatic (gray components). We decompose the tonal colors into seven components, depending on their hue angle range, as shown in Table 1. These are empirically found after choosing red at $R(x_r = 0.674, y_r = 0.326)$ in the chromaticity diagram. The average

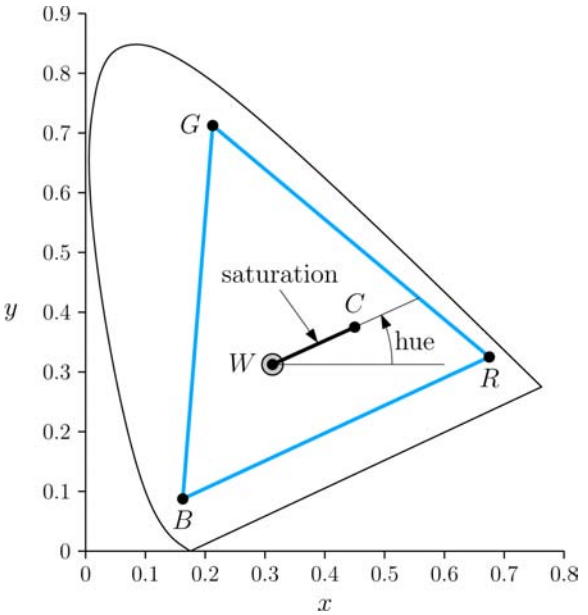

Fig. 8. Chromaticity diagram. $W(x_w = 0.310, y_w = 0.316)$ is the white point, and $R(x_r = 0.674, y_r = 0.326)$, $G(x_g = 0.216, y_g = 0.716)$, $B(x_b = 0.162, y_b = 0.090)$ are the vertices of the color gamut. The circle around W is the achromatic region with radius $s_{th} = 0.02$. $C(x_c, y_c)$ is a sample chromatic value.

Table 1. Hue angle ranges of tonal colors considered in our work.

#	Color index	Hue angle range	Color
1	H_{c1}	0°–83°	Red (high)
2	H_{c2}	84°–86°	Red (low)
3	H_{c3}	87°–121°	Orange
4	H_{c4}	122°–151°	Yellow
5	H_{c5}	152°–275°	Green
6	H_{c6}	276°–333°	Blue
7	H_{c7}	334°–360°	Violet

hue, h_{avg}, and a linear combination of average saturation, s_{avg}, and maximum saturation, s_{max}, given by $\nu s_{max}[i] + (1 - \nu)s_{avg}[i]$ for ith color, are considered to modify the hue and saturation of the chromatic pixels present in the mural image, as shown in Algorithm 1. We empirically set $s_{th} = 0.02$ and $\nu = 0.3$. Although tonal processing suffers from some discontinuities at certain portions of the digitally restored image, it provides much better color cues while recreating the mural images by an artist. Fig. 9 (middle) shows one such example of tonal processing.

Unlike the color transfer methods,[44–48] tonal processing does not require any reference image or color palette to transfer the style or color onto a target image.

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Algorithm 1: Tonal processing by hue-saturation analysis.

Input: Inpainted image, I_{RGB}.
Output: Tonal processed image, I_{RGB}^{mod}.

Convert the RGB image (I_{RGB}) to CIE-XYZ image (I_{XYZ}).
Compute the hue, $h(p)$, and saturation, $s(p)$, $\forall\, p \in I_{XYZ}$.
Define the hue ranges, H_{ci} $\forall\, i \in \{1, 2, \ldots, 7\}$.
for $i \leftarrow$ *1 to 7* **do**
  $s_{avg}[i] \leftarrow 0$, $h_{avg}[i] \leftarrow 0$, $count[i] \leftarrow 0$
  for *each pixel* $p \in I_{XYZ}$ **do**
    if $s(p) > s_{th}$ AND $h(p) \in H_{ci}$ **then**
      $s_{avg}[i] \leftarrow s_{avg}[i] + s(p)$, $h_{avg}[i] \leftarrow h_{avg}[i] + h(p)$
      $count[i] \leftarrow count[i] + 1$
for $i \leftarrow$ *1 to 7* **do**
  $h_{avg}[i] \leftarrow h_{avg}[i]/count[i]$, $s_{avg}[i] \leftarrow s_{avg}[i]/count[i]$
  $s_{new}[i] \leftarrow \nu \cdot s_{max}[i] + (1 - \nu) \cdot s_{avg}[i]$
for *each pixel* $p \in I_{XYZ}$ **do**
  for $i \leftarrow$ *1 to 7* **do**
    if $h(p) \in H_{ci}$ **then**
      $h_{mod}(p) \leftarrow h_{avg}[i]$, $s_{mod}(p) \leftarrow s_{new}[i]$
Update I_{XYZ} to obtain I_{XYZ}^{mod}, using $h_{mod}(\cdot)$ and $s_{mod}(\cdot)$.
Convert I_{XYZ}^{mod} to I_{RGB}^{mod}.

Fig. 9. Results on the mural image `VARAHA`. Left: Original. Middle: Repainted image after tonal processing. Right: After texture fusion.

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It uses the color information inherent in the source image, and hence preserves the originality of the artwork.

6.2. *Texture fusion*

The process of filtering, which is essentially a low-pass filtering in the present context, causes the inherent texture in the mural images to get diminished, since they contribute as high-frequency components in the image. Though the scaling parameters of the filter are different and independent for foreground and background, the presence of texture poses as noise to the basic bilateral filter, which thereby gets filtered off along with other degrading noise factors, as discussed in Secs. 2 and 5. As a result, the image loses its natural appeal, and is rather perceived as pale and synthetic. Hence, to restore its natural glaze, a general texture of murals is chosen, and it is synthesized to fit the size of the mural image by a process of patch-based texture synthesis, known as *image quilting*.[22,23,49] The fused composite image holds the details of both the texture and the repainted image.[50] In our work, the given texture is synthesized on patch basis with minimum error boundary cut, which reduces the block artifacts caused by misalignment of neighboring patches.[23] Although the glaze of texture could be achieved using texture-transfer methods, it would also perturb the structure information of the mural image.[23,39,51] So, gradient-based fusion of synthesized natural texture is sought for texture rendering.

The synthesized texture is fused with the mural image to deliver a natural glaze to the repainted image. The fusion is achieved by *merging of gradients*.[21,52] The gradient of the luminance component of the texture image and the gradient of the mural image, repainted so far, are *alpha-blended* with convex combination of the gradient values. Pixel-wise fusion of intensity values of the image would cause a bias in the color of the fused mural image with color fading and color artifacts, resulting in a poorer appearance. On the contrary, the gradient-based fusion reduces fading due to the fusion process, since the bias intensity would become redundant in gradient domain.

The intensity image of the mural after texture fusion, I_{fuse}, is obtained by the texture-fused gradient image of the mural, G_{fuse}. Let the repainted image of mural before fusion be denoted by I_{rpt} and the texture image by I_{tex}. Let G_{rpt} and G_{tex} be the gradient images of I_{rpt} and I_{tex} respectively. These gradient values are alpha-blended (the value of α is empirically chosen as 0.7) to obtain the fused gradient image $G_{fuse}(x, y)$ as follows:

$$G_{fuse}(\mathsf{p}) = \alpha \cdot G_{rpt}(\mathsf{p}) + (1 - \alpha) \cdot G_{tex}(\mathsf{p}) \quad \forall\, \mathsf{p} \in I \setminus \beta, \tag{6}$$

where β is the boundary of the input image, I.

To obtain an approximation of the texture-fused image I_{fuse}, subject to least-square error, we minimize the function $f(\cdot)$, which is defined as the sum of squared differences between the corresponding intensity values of the fused gradient image,

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G_{fuse}, and those of the gradient field of reconstructed image, ∇I_{fuse}. Mathematically, we minimize

$$f(\nabla I_{fuse}, G_{fuse}) = \sum_{\mathsf{p}\in I}\left(\left(\frac{\partial I_{fuse}(\mathsf{p})}{\partial x} - G^{(x)}_{fuse}(\mathsf{p})\right)^2 + \left(\frac{\partial I_{fuse}(\mathsf{p})}{\partial y} - G^{(y)}_{fuse}(\mathsf{p})\right)^2\right), \quad (7)$$

where $G^{(x)}_{fuse}(\mathsf{p})$ and $G^{(y)}_{fuse}(\mathsf{p})$ are the respective x and y components of $G_{fuse}(\mathsf{p})$.

The solution to Eq. (7) is obtained by solving the Poisson equation given as follows[52,53]:

$$\left(\frac{\partial^2 I_{fuse}(\mathsf{p})}{\partial x^2} - \frac{\partial G^{(x)}_{fuse}(\mathsf{p})}{\partial x}\right) + \left(\frac{\partial^2 I_{fuse}(\mathsf{p})}{\partial y^2} - \frac{\partial G^{(y)}_{fuse}(\mathsf{p})}{\partial y}\right) = 0$$
$$\text{or,} \quad \nabla^2 I_{fuse}(\mathsf{p}) = \text{Div}(G_{fuse}(\mathsf{p})), \quad (8)$$

where, Div$(\cdot)$ is the divergence operator, and $\nabla^2 I_{fuse}$ is the Laplacian of I_{fuse}. In the intensity image to be reconstructed, the boundary values are assigned to be same as the boundary values of I_{rpt}. That is,

$$I_{fuse}(\mathsf{p}) = I_{rpt}(\mathsf{p}) \quad \forall\, \mathsf{p} \in \beta. \quad (9)$$

By computing the eigenvalues of G_{fuse} at each point p, the intensity image can be obtained by Eq. (10), using the Dirichlet boundary condition of Eq. (9).[52]

$$I_{fuse}(\mathsf{p}) = \text{IDST}\left(\text{DST}\left(\frac{G_{fuse}(\mathsf{p})}{\lambda}\right)\right) \quad \forall\, \mathsf{p} \in I, \quad (10)$$

Fig. 10. Texture rendering results. Left: Texture transfer. Right: Gradient based texture fusion.

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Fig. 11. Left: Repainted image before texture fusion. Middle: Intensity-based fusion. Right: Gradient-based fusion.

where DST is the discrete sine transform, IDST is the inverse DST, and λ is the eigenvalue of G_{fuse}. Finally, the intensity of the reconstructed image, I_{fuse}, is normalized to $[0, 255]$. The fusion of mural texture poses the repainted mural image to appear in a more natural form to be perceived, as evident from the images in Fig. 9. The images in Fig. 10 justify the choice of gradient based texture fusion technique, where the structure remains unperturbed, unlike texture transfer method.[23] Also, gradient based texture fusion is preferred over intensity based texture fusion to avoid the bias luminance component in the resultant image. Comparative results are shown in Fig. 11.

7. Results and Evaluation

We have done our experimentations on a set of color images of mural paintings taken at Virupaksha Temple, Hampi. Each image has been subjected to the integrated

(a) (b)

Fig. 12. Demonstration of our integrated repainting process (*continued to next page*). (a) Original image (`LAKSHMI-NARAYANA`), (b) preprocessed image, (c) after bilateral filtering, (d) segmentation mask, (e) inpainted image, (f) final image after tonal processing and texture fusion, (g) artist's recreation by considering only the original image and (h) artist's recreation by considering both the original and the repainted images.

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(c)

(d)

(e)

(f)

(g)

(h)

Fig. 12. (*Continued*)

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processing of histogram stretching, gamma correction, image inpainting, bilateral filtering, image sharpening, color constancy recovery, tonal processing, and texture fusion, as discussed in this paper. The implementation has been made using MATLAB (R2009a) on a standard PC (Intel Pentium-4 HT CPU, 2.99 GHz, 3 GB RAM) in Windows environment. A stage-by-stage demonstration on a typical image is shown in Fig. 12. Figure 12(a) shows the degraded painting of the mural in original form. Figure 12(b) is the preprocessed form of the image, which, after noise reduction by scaled bilateral filtering, improves to the image shown in Fig. 12(c). Figure 12(d) is the segmentation mask generated by the GrowCut algorithm, which is used in subsequent processing stages.[15] Figure 12(e) is the repainted image with a uniform background and sharp foreground. At this stage, the blemished background is restored to the anticipated form, soft and uniform, without disturbing the originality. Figure 12(f) is the post-processed final image after tonal processing and texture fusion. Here, after repainting process, the background is scaled down by a factor of 4, and the parameters for the bilateral filter are $\sigma_G = 0.5$, $\sigma_s = 24$, and $\sigma_r = 28$. In Fig. 12(g), we have shown the image of the painting based on the artist's perception of only the original image. Figure 12(h) shows the image of the painting furnished by considering the original image, in addition to the image produced by our digital restoration algorithm (Fig. 12(f)). Clearly, the second painting is much brighter and bolder, which is also evident from a similar result presented in Fig. 1. To demonstrate the robustness, two more sets of results are shown in Fig. 13.

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7.1. *Evaluation techniques*

Unlike metric-based assessment, the evaluation of the proposed repainting method is made on a subjective basis by considering a collection of individuals as evaluators.[54–56] Such psychophysical evaluation is usually practiced to assess the performance of image rendition techniques, e.g. see Ref. 57. As the qualitative evaluation is inherently subjective, we have used paired comparison technique[55] to minimize the bias and to maintain the simplicity of the evaluation process. The evaluators are shown two images simultaneously, which are outputs from two distinct processes or two distinct stages of a particular process, and they are asked to choose the one perceived to be better. For each original image, the corresponding set considered for evaluation comprises the following four images:

(i) Candidate *enhn*: enhanced image after preprocessing stage.
(ii) Candidate *inpt*: post-processed inpainted image.[16,42]
(iii) Candidate *rptc*: color-translated repainted image without texture fusion.
(iv) Candidate *rptx*: color-translated repainted image after texture fusion (final output of our integrated approach).

Each evaluator finally chooses the best perceived in that set, based on pairwise comparison.

Fig. 13. Repainting results by our algorithm on the image `HANUMAN-NANDI` (top row) and `SAKHI` (bottom row). Left: Original image. Right: Final repainted image.

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For several procedural stages applied on a large set of images, the number of candidates is quite large. Hence, instead of comparing every pair of results, three different tournament approaches are followed to assess the quality of output images. These are *knockout tournament*, *challenging tournament*, and *round-robin tournament*. A *player* in each such tournament corresponds to an output of some algorithm.

Knockout tournament has a simple and familiar format. The players correspond to the leaf nodes of a binary tree, and the winners of the pair-wise competition among the sibling nodes move up the tree. The final winner is the one who reaches the root of the tree. In the challenging tournament, two players are randomly chosen. The loser is eliminated from the tournament and the winner goes to the next round. One randomly chosen player from the rest then plays with this winner. The player who never loses, is the final winner. In the round-robin tournament, each player

meets all the other players in turn in a single round-robin schedule, and the winner is the one having maximum wins.

To adjudge the merit of our integrated repainting system, a voting system is finally used by us to decide the ranking of the players in the tournaments played.[58,59] To avoid a tie-breaker whenever there is a tie between the qualitative measures of two algorithms, we use the voting system proposed in Ref. 58. This method of voting system selects a single winner using the votes that express preference, which is explained next.

7.2. *Evaluation strategy*

Let $d(a, b)$ be the number of voters who strictly prefer candidate a to candidate b. A *path* from a candidate u to a candidate v of *strength* ψ is a sequence of candidates, namely $\langle u := c_1, c_2, \ldots, v := c_k \rangle$, with the following properties:

(i) $d(c_i, c_{i+1}) > d(c_{i+1}, c_i)$, $\forall\, i \in \{1, 2, \ldots, k-1\}$.
(ii) $d(c_i, c_{i+1}) \geq \psi$, $\forall\, i \in \{1, 2, \ldots, k-1\}$.
(iii) There exists an $i \in \{1, 2, \ldots, k-1\}$ such that $d(c_i, c_{i+1}) = \psi$.

The strength of the *strongest path* from candidate u to candidate v is denoted by $\psi_{\max}(u, v)$. It is the maximum value of the strengths of all possible paths from candidate u to candidate v. If there exists no path from candidate u to candidate v, then $\psi_{\max}(u, v) = 0$. So, u is assessed as a better candidate than v if and only if $\psi_{\max}(u, v) > \psi_{\max}(v, u)$. Candidate u is reported as a potential winner if $\psi_{\max}(u, v) \geq \psi_{\max}(v, u)$, for every other candidate v.

7.3. *Evaluation experiment*

We have performed the experiment of evaluation with twelve individual evaluators playing the tournament approach of subjective evaluation, with reference to each original image. Ages of these evaluators are from 21 to 54 years. There are eight males and four females, none of them showing any colorblindness on medical test. The height and the width of the test images vary from 600 to 1200 pixels. They have been displayed in the laboratory environment with normal fluorescent lighting on a touchscreen 17″ LCD monitor, AOC make, model 177Sa, resolution 1280×1024 dpi.

Each experiment is performed on twelve sets containing four images, each image being from one of the four categories, as mentioned earlier. Each evaluator considers each of the twelve sets one by one. For each pair of images chosen randomly from the set under consideration, the evaluator assigns 1 to the better image and 0 to the worse.

After comparing different categories of images over all twelve sets, a matrix of strengths of strongest paths is obtained by the evaluation strategy explained in Sec. 7.2. Table 2 shows the strengths of strongest paths for the evaluation done by evaluators, with reference to the considered methods, for the integrated process.

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Table 2. Strengths of strongest paths from the evaluation experiment.

$\psi_{\max}$	$\psi_{\max}(*, enhn)$	$\psi_{\max}(*, inpt)$	$\psi_{\max}(*, rptc)$	$\psi_{\max}(*, rptx)$
$\psi_{\max}(enhn, *)$	0	2	3	4
$\psi_{\max}(inpt, *)$	29	0	8	0
$\psi_{\max}(rptc, *)$	45	42	0	5
$\psi_{\max}(rptx, *)$	66	99	129	0

Each evaluator is allowed to play all three tournaments, and the strengths of the strongest paths are obtained by considering the votes from all the evaluators for the three tournament strategies.

From Table 2, it is evident that candidate *enhn* is better than candidate *inpt*, *rptc* is better than candidate *enhn*, and candidate *rptx* is better than candidate *rptc*. In short, candidate *rptx* is the potential winner, which implies that the repainting approach with texture fusion is perceived relatively better in comparison with the other processes of restoration.

8. Conclusion

We have shown how an integrated system can be designed to digitally restore the images of century-old murals, without losing their artistic information and other artifacts. The work related with the proposed system is based on integrating an ensemble of classical as well as state-of-the-art image processing techniques, including image enhancement, denoising, segmentation, scaling, filtering, digital inpainting, bilateral filtering and sharpening, along with restoration of colors using color constancy, a novel technique of tonal processing, and texture rendering based on gradient fusion. The outcome of the integrated approach of image repainting is subjectively evaluated through various stages by different individual evaluators on the basis of three different tournament approaches, followed by a strategy for evaluation of the potential winner.

The integrated approach used to restore the murals assumes the background to be uniform. Otherwise the method becomes too complex for images having distinct structures in the background. First, the seeding process for segmentation requires heavy manual intervention. Secondly, the source-constrained inpainting process requires multiple sources to restore the image satisfactorily. Though this can be accomplished by the integrated approach by repeating the current process a number of times, manually supervising the process every time becomes a highly tedious task.

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